Research

Analyzing the impact of artificial intelligence on the online purchase decision-making process through the lens of the UTAUT 2 model

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Abstract
Consumer perceptions and purchasing decision-making have been significantly impacted by the rapid use of artificial intelligence (AI) in the online retail sector. The online shopping experience has been transformed by AI technologies, which include sophisticated product evaluation algorithms, individualized purchasing recommendations, and improved customer care. To better understand the deep interactions between factors linked to artificial intelligence and customer decision-making processes, this study investigates the complex adoption landscape of AI within the Delhi-NCR online retail industry using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) framework. The research employs a quantitative methodology by applying Structural Equation Modelling (SEM) through SmartPLS 4 to evaluate key behavioral variables. The results reveal that Behavioral Intention (BI) has a strong and significant impact on Usage Behavior (UB). Trust in AI systems emerged as a critical factor affecting BI. Significant factors like Habit, Hedonic Motivation, Trust, and Personal Innovativeness emerged as pivotal in shaping consumers' Behavioral Intentions towards AI in online shopping. Perceived Risk showed a marginally negative effect on BI, suggesting consumers' hesitation in adopting AI for online shopping. However, factors such as Social Influence and Effort Expectancy had negligible impacts on BI, contrasting with prior research. These findings suggest that consumer trust, delight, and habitual AI usage are more influential than usability or social pressures for AI enabled e-commerce landscape.

Keywords Artificial intelligence · UTAUT · Personalized recommendation systems · Consumer decision making · Acceptance and adoption of AI

1 Introduction

AI has emerged as a key driver in revolutionizing the retail industry, especially in the realm of online shopping [1]. Retailers are using AI technology to improve customer support, product appraisal, and personalized suggestions among other elements of the online shopping experience [2]. The decision-making process for online purchases is fluid and dynamic, with each option resulting in a unique trip for the person. The decision-making process for online shoppers, particularly millennials, has been influenced by the availability of many purchasing channels and the capacity to seek for novelty, expertise, and inspiration [3]. A variety of elements significantly influence people's decision to make an online purchase. To study the acceptance and adoption of AI in online purchasing, various models have been developed. One such model

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that was created as a comprehensive framework of technology acceptance and use across diverse contexts is the Unified Theory of Acceptance and Use of Technology (UTAUT) [4] and UTAUT 2 which extends the scope of UTAUT [5] in terms of strengthening its explanatory ability.

This study shall leverage the UTAUT 2 model as a theoretical framework to decipher the factors that influence AI adoption within the e-commerce domain with specific emphasis on the personalized recommendation systems influencing the decision-making process of consumers in Delhi-NCR. The study adds an additional construct Personal Innovativeness to the basic model and will study the impact of these constructs on the decision-making process of consumers during online shopping. The study aims to illuminate the intricate interplay between AI-related variables and the decision-making processes of consumers.

According to [6], 64% of people on the planet use the internet, and the number of people who shop online is growing regularly. Moreover, e-commerce has become a crucial component of international buying in recent years. Since the internet's inception, the purchasing and selling of commodities has experienced significant transformation, much like many other industries. Today's consumers enjoy the benefits of online activities due to the growing digitalization of modern life. How consumers and sellers communicate has changed dramatically as a result of consumer behaviour on the Internet [7].

The competitiveness between organizations has intensified due to the advancement of digital technology [8]. Businesses can now easily and economically communicate directly with the clients they seek to serve on a worldwide scale, thanks to the expanded number of communication channels accessible [9]. By the end of 2026, it is expected that online sales in the retail sector would have accounted for 24% of all online sales, up from 20.8% of all internet sales to this point [10]. Customers have been bewildered by the firm's array of offerings since they are easier to reach [11]. Today's consumers have a plethora of options, and the capacity to analyse items and receive product information makes adopting personalized services even more crucial for businesses [12, 13] suggests that businesses need to understand customer behaviour if they want to flourish in the online retail market.

When diversification is thus extensive, the solutions are customized for every customer [12]. Companies can provide each customer individualized services by using the data they have collected. As per a global study of company managers, 37% of them stated that their organizations solely used first-party data to customize customer experiences [14]. Consequently, corporations are now able to construct consumer profiles based on their purchasing patterns thanks to the utilization of in-house data and the sourcing of digital records from customers [15]. According to [16], forty percent of consumers worldwide indicated that they would like companies to better understand their personal style preferences and what befits them. Consumers' decisions to make future online purchases may be significantly influenced by their online shopping experiences, and their concerns about privacy may also have a big influence [17].

Following a personalized online experience, 60% of customers reported they could make purchases again in 2021, and 49% of customers stated they shall be motivated make additional purchases from a store that offered online personalization in 2022 [18].

Personalization can take several forms and the form that has been studied in this study are the Personalized Recommendation Systems. The research lies at the intersection of artificial intelligence, consumer behaviour, and technology acceptance. The research seeks to explore the how the adoption and utilization of artificial intelligence (AI) shall influence the process of decision making during online purchases with respect to shoppers residing in Delhi-NCR, India. The study will use the UTAUT 2 (Unified Theory of Acceptance and Use of Technology) model as the theoretical framework.

The UTAUT 2 model integrates various constructs such as effort expectancy, performance expectancy, facilitating conditions and social influence from the basic UTAUT Model, adds additional constructs such as habit, price value and hedonic motivation. Various researchers have added constructs such Technology fear, Trust and Perceived Risk to improve the explanation capacity of the model. This study removed Technology fear but added Personal Innovativeness to improve the explanation capacity of the model.

Personalized recommendation systems, which leverage AI algorithms to provide tailored product or service suggestions to users, have become integral in e-commerce platforms. These systems aim to enhance user experience, increase engagement, and ultimately influence purchase decisions. The research considers the specific cultural and socio-economic context of Delhi-NCR, acknowledging unique characteristics of the region, such as the emergence of a new middle-income segment, the impact of medical tourism, and the adoption of app-based services. These contextual factors can significantly influence consumer behaviour and technology acceptance, thereby shaping the influence of AI on online purchase decision-making process.

With this context the research questions proposed for this research are as below:

RQ-1: How well does the UTAUT 2 model explain the adoption of AI within the e-commerce sector of Delhi-NCR
RQ-2: Which UTAUT2 constructs are the most influential in impacting the process of decision-making of consumers in the context of AI enabled online shopping and what is the impact?

The study's findings shall highlight several key factors that influence the adoption of AI by consumers in online shopping, particularly in the Delhi-NCR region. These insights from this research will present a nuanced estimation of the factors shaping incorporation of AI in e-commerce landscape.

2 Conceptual background

2.1 Personalized recommendation systems

Predicting a user's preferences or interests and offering tailored recommendations is the goal of customized recommendation systems, a subset of information filtering systems [19]. By providing customized recommendations for goods or services, these systems aim to enhance customer relationship management and tackle the growing issue of online information overload [19]. To improve user experience and engagement, they have been vastly applied in a variety of domains, including e-commerce, online retail, and entertainment platforms [20]. Collaborative filtering, which involves gathering user preferences from several users through groups working together, is one of the main strategies utilized in personalized recommendation systems [21]. This process makes automatic predictions about a user's interests.

Major e-commerce sites like Amazon and Alibaba have used this strategy to recommend products to consumers guided by their past choices and habits [22]. Moreover, the integration of personality elements into recommender systems has been contemplated as a means to augment the level of personalization of suggestions, enhance the overall quality of recommendations, thereby improving the user experience [23]. Additionally, the use of personalized recommendation systems has demonstrated notable increases in sales, particularly in the book, movie, and CD industries, where sales increases of 2% to 8% have been observed [24]. This demonstrates how well customized recommendation systems work to change customer behaviour and purchasing choices. Furthermore, it has been discovered that the application of cloud computing technology improves the scalability, effectiveness, and precision of e-commerce recommendation algorithms by resolving problems like sparsity and real-time recommendation concerns [25].

Personalized recommendation systems have been used not only in e-commerce but also in a variety of other fields, including music preferences, restaurant recommendations, and e-learning, proving the adaptability and broad reach of these systems [26–28]. The ability of personalized recommendation systems to adapt to various domains is demonstrated by the development of semantic recommendation systems for e-learning and the integration of trust-based recommender systems for personalized restaurant recommendations [26].

2.2 Consumer behaviour and expectations in online shopping

Several studies show that a range of factors influence the expectations and behavior of consumers when they shop online [29] discovered attitudes toward e-shopping are strongly influenced by perceived usefulness (PU) and perceived ease of use of trading online (PEOUT) [30] investigated the association between demographic variables and the online shopping behavior, illuminating the role of age, gender, income, education, occupation, and marital status [31] highlighted the influence of previous online shopping experience on consumers' intention to purchase online. Customers' increasing empowerment in online commerce has led to higher expectations and demands in purchasing experiences, according to [31, 32]. In general, attitudes, confidence, ease of use, effort, demography, prior experiences, and growing consumer empowerment all have an impact on the behavior and expectations of customers when it comes to online purchasing.

2.3 AI in the decision-making process

The process of decision making for purchases has significantly changed owing to the growing use of artificial intelligence in the online retail sector. Retailers have embraced AI technology to improve a number of elements of the online shopping experience, including product evaluation, individualized suggestions, and customer assistance [2]. The ability of AI to "accurately interpret external data, learn from it, and apply those insights to accomplish specific goals and tasks with flexible adaptation" [33] is revolutionizing e-commerce. AI can take the form of a system, tool, technique, or algorithm, depending on the situation [34–36]. Apriori algorithm for mobile e-commerce recommendation systems, picture recognition for visual search, NLP for chatbots, and recommendation algorithms are only a few examples of the AI technologies frequently used in the e-commerce industry.

2.4 AI based application in businesses

On one hand, the application of AI offers businesses the chance to acquire a competitive edge by utilizing big data to specifically cater to the needs of their clients through individualized services [37]. The deployment of algorithmic AI agents, which influence consumer decision-making, is another application of AI in the online retail sector. These algorithmic agents' autonomy may have an impact on consumer purchasing choices. Self-determination theory-based research has looked at how various AI algorithmic decision-making roles affect consumer purchase choices [38]. However, the use of AI technologies by consumers is crucial for the successful integration of AI in online services, therefore the success of these technical fusions heavily depends on this.

2.5 Acceptance and Adoption of AI in Online Commerce

Acceptance guarantees that users will engage with AI-driven features and that merchants will see the benefits of AI technology. Adoption entails the effective integration of AI into the operations and platforms of online commerce, producing observable advantages for both customers and merchants. The level of AI adoption and acceptance in online purchasing can vary by region, sector, and the particular AI applications being employed. The degree of acceptance and adoption of AI can be affected by variables like privacy issues, the effectiveness of AI implementations, and effective communication of AI benefits. Researchers and professionals have utilized a variety of theoretical frameworks to examine the acceptance and use of AI in online buying. They shed light on the variables impacting customer behaviour, such as perceived usefulness, ease of use, social influence, facilitating conditions, hedonic motivation, trust, etc.

According to a study by [39] of the AI adoption in the online grocery shopping in China, the attitudes and purchase intentions were correlated positively with the perceived incentives and correlated negatively with perceived complexity. Additionally, based on consumers' preferences for particular food categories, separate customer groupings were identified. The study stressed the need of comprehending consumer behaviour in order to satisfy their wants and succeed in the market for online food purchasing. The accuracy, understanding, and engagement experience of AI marketing technology favourably influenced consumers' perceived utility value and hedonic value, eventually promoting purchase intention.

The study by [40] on the uptake of online grocery shopping by consumers it was discovered that diverse groups of consumers who had adopted the practice, each with their own preferences and reasons for doing so. They stressed the need of retailers comprehending consumer behaviour and preferences in order to enhance the convenience of online food buying. Gender played a role in attitudes about financial security, according to [41] investigation of the impact of demographic characteristics on perceived risks on attitudes toward online shopping.

[42] in 2021 studied the use of AI in online shopping platforms. They studied the impact of various functional AI experiences on the purchase intentions on consumers using a structural equation model. The study made a point of emphasizing the significance of perceived value as a mediating factor in the connection between AI experience and purchase intention [43] looked at how views regarding online purchasing among Indian women consumers are shaped by perceived benefits like price, convenience, and variety. The study underscored how crucial it is to comprehend the particular elements that influence Indian consumers' opinions toward internet buying. They emphasized the necessity for future study to examine attitudes toward internet purchasing among various groups and genders and to take the geographical environment into account.

2.6 Research Gap

Most of the literature, which has been written about the UTAUT2, has concentrated on different technologies, including web-based services, online shopping and mobile banking [47]. Nevertheless, there exists a dearth of comprehensive research that integrates the UTAUT2 model with the assessment of the impact of AI on the online purchase decision-making process in the particular geographical context of Delhi-NCR, despite studies that have examined the effect of AI focused on consumer intent to purchase in e-retailing [48], AI's effect on return policies in online shopping [49], and the role of perceived value in mediating the effects of AI and digital marketing on purchase intention [50].

There is also research gap in the usage of PLS-SEM specifically to examine the effect of AI on the online purchase decision-making process in Delhi-NCR region, despite studies using PLS-SEM to address endogeneity concerns in international marketing applications [51] and to analyse the factors that drive consumers' purchase intentions on digital business model platforms [52]. Additionally, factors that affect how consumers perceive online shopping [53], the relationship between gamification, e-service quality, e-trust, and online purchasing decisions [54], and aspects that shape purchase behaviour in mobile gaming environments [55] have been studied in the literature that is currently available.

The precise elements and constructs in the UTAUT2 model that are pertinent to the impact of AI on the decision-making process for online purchases in the Delhi-NCR region, however, remain little understood.

Consequently, the research gap serves as the motivation behind this study. The authors have conducted an extensive study that applies the PLS-SEM technique to analyse AI's influence on the process of making decisions for online purchases while integrating the UTAUT2 model and concentrating on the particular geographic context of Delhi-NCR. The authors have also identified the specific constructs of UTAUT2 that are pertinent to the decision-making process in identified context.

3 Hypothesis development and conceptual framework

The decision-making process for online purchases is fluid and dynamic, with each option resulting in a unique trip for the person. The decision-making process for online shoppers, particularly millennials, has been influenced by the availability of many purchasing channels and the capacity to seek for novelty, expertise, and inspiration [3]. A variety of elements significantly influence people's decision to make an online purchase. To study the acceptance and adoption of AI in online purchasing, various constructs need to be considered. The UTAUT2 theoretical model states that technology use is determined by Behavioral intention which can be perceived as the possibility of technology adoption. Behavioral intention is influenced directly by ten fundamental constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), Habit (H), Personal Innovativeness (PI), Trust (TR) and Perceived Risk (PR). The UTAUT2 faced criticism claiming that the model is complex. The moderators, such as gender, age, experience, and voluntariness of use, influence of the predictors and increase the explanatory power but also intensify the model complexity. Thus, the model is often applied without moderators. This authors in this study also do not consider these moderators as proposed in the UTAUT2 model by [56].

3.1 Behavioral intention and effort expectancy

As stated by [44], effort expectancy refers to the level of ease with which a system may be used. Perceived usability and complexity are the building blocks of effort expectation, and these factors are derived from TAM, MPCU, and IDT, which have definitions and scales that are identical. After prolonged use of technology, the effect of construct becomes insignificant [57, 58]. Based on this information hypothesis 1 has been stated:

Hypothesis 1 Effort Expectancy positively influences the Behavioral Intention (EE—> BI) of PRS in online buying.

3.2 Facilitating conditions and its relation to behavioral intention and use

Facilitating conditions refer to the extent to which a person believes that a corporation and its technological infrastructure are in place to enable system use [44]. The facilitating conditions construct arises from the amalgamation of compatibility, perceived behavioral control, and facilitating conditions from TPB, CTAMTPB, MPCU, and IDT. Positive conditions directly enhance the intention to use, although this effect weakens after the initial usage. Accordingly, the model proposes that favorable conditions have a direct and substantial impact on people's technology use [44]. Based on this information the hypothesis 2 has been stated:

Hypothesis 2a Facilitating Conditions positively influence Behavioral Intention (FC—> BI) of PRS in online buying.

Hypothesis 2b Facilitating Conditions positively influence Use (FC—> UB) of PRS in online buying.

3.3 Habit and its relation to behavioral intention and use

According to [56], habit refers to "the degree to which individuals are inclined to engage in behaviors automatically" [56] proposed that habit could influence actual use both directly and indirectly by means of behavioral intention. The impact of either connection, however, depends on to what extent people rely on routine behavior while embracing or utilizing technology [46, 56]. Based on this information the hypothesis 3 is stated below:

Hypothesis 3a Habit positively influences the Behavioral Intention (H—> BI) of PRS in online buying.

Hypothesis 3b Habit positively influences the use (H—> UB) of PRS in online buying.

3.4 Hedonic motivation and behavioral intention

According to [56], hedonic motivation refers to "the pleasure or delight from using technology, which plays an essential role in influencing both its acceptance and usage."

Hypothesis 4 Hedonic Motivation positively influences the Behavioral Intention of PRS in online buying (HM—> BI).

3.5 Performance expectancy and behavioral intention

According to [44], Performance expectancy refers to "the extent to which an individual believes that using the system will improve their job performance". Models as TAM, TAM2, CTAMTPB, MM, MPCU, IDT, and SCT—specifically suggest that the bases of performance expectancy are perceived utility, extrinsic motivation, job suitability, relative benefit, and outcome expectations. It is the best indicator of usage intention and substantial in both required and optional situations [59, 60]. Based on this information the hypothesis 5 is stated below:

Hypothesis 5: Performance Expectancy positively influences the Behavioral Intention of PRS in online buying (PE—> BI).

3.6 Personal innovativeness and behavioral intention

Research of [61], serves as the foundation for personal innovativeness. They concluded that some people "adopt IT innovations earlier than others" [61] and that these individuals are crucial in the spread of new technologies. This is particularly crucial for AI-powered goods and services. It takes a certain level of curiosity and openness to try new things before consumers will even consider utilizing a new product or technology. Based on this information the hypothesis 6 is stated below:

Hypothesis 6 Personal Innovativeness towards products/services containing AI, positively influences the Behavioral Intention (PI—> BI).

3.7 Perceived risk and behavioral intention

Perceived Risk (PR) refers to the extent to which users consider that using AI in online shopping can cause possible loss. Perceived Risk (PR) showed a marginally significant negative impact, suggesting that consumers are hesitant to use AI when they shop online [62]. Based on this information the hypothesis 7 is as below:

Hypothesis 7 Perceived Risk negatively influences the Behavioral Intention of PRS in online buying (PR—> BI).

3.8 Price value and behavioral intention

Price value refers to "the trade-off consumers make between the advantages they perceive from the applications and the monetary cost associated with their use." [56], was used to represent the cost aspect. Incorporating cost into the new model was warranted due to its greater relevance in consumer product use rather than in business technology utilization. According to [56], there are no immediate financial ramifications for users in the latter scenario. On the other hand, when using technology comes with tangible costs, customers feel more responsible. The more intense the use of technology, the lower the expenses [56] [63]. Based on this information, the hypothesis 8 is stated below:

Hypothesis 8 Price Value positively influences the Behavioral Intention of PRS in online buying (PV—> BI).

3.9 Social influence and behavioral intention

Social Influence (SI) is defined as the extent to which an individual's decision to use a new system is shaped by the influence of others [44]. It aligns with similar constructs such as subjective norms, social factors, and image in TRA, TAM2, TPB, CTAMTPB, MPCU, and IDT. SI has a greater effect when technology usage is necessary [44], in which case people may use it for compliance purposes rather than according to their own preferences [45]. This can help explain the inconsistent performance of the construct in subsequent research for model validation [58, 59]. With this backdrop, hypothesis 9 is stated:

Hypothesis 9 Social Influence positively influences the Behavioral Intention of PRS in online buying (SI—> BI).

3.10 Trust and behavioral intention

Trust is the belief of an individual in a system that nothing wrong will happen. Trust in AI systems for online shopping leads to an intent to use the system for purchasing and making payment without any hesitation and second thoughts. With this backdrop hypothesis 10 is stated:

Hypothesis 10 Trust positively influences the Behavioral Intention of PRS in online buying (TR—> BI).

3.11 Behavioral intention and use

In the UTAUT model, technology use is directly influenced by behavioral intention. Behavioral Intention leads to actual use of technology for online shopping. With this backdrop hypothesis 11 is stated:

Hypothesis 11: Behavioral Intention of PRS in online buying positively affects Use (BI—> UB).

Compared to other technology adoption models [64], UTAUT2 has greater predictive potential because it demonstrates that the suggested components account for 70% of the variance in usage intention [44]. The interactive effects of multiple variables, along with personal and demographic traits, reveal the complexity of technology adoption [44]. Age, gender, experience, and conscious usage moderate the impact of predictors on intention [44]. The current study does not consider the impact of the moderators specified in the original UTAUT2 model [56]. Figure 1 shows the Conceptual model, adapted from the UTAUT2 model, used in this study.

4 Research methodology

4.1 Research design

The study has adopted Exploratory Sequential Design involving Quantitative analysis of data. The work begins with exploratory research to gain insights about the current state of AI adoption and how it can impact the consumer buying decisions in Delhi-NCR. Next Descriptive Research is conducted via a questionnaire and subsequent data collection. Explanatory Research followed to comprehend the causal relationship between AI related variables and consumer decision making. This phase involved statistical analysis and hypothesis testing which is done using SEM-PLS. The structured questionnaire designed on the basis of the constructs of the original UTAUT model [44] and the extended UTAUT2 model was circulated to the user population in Delhi NCR and the primary data collected analysed using statistical techniques which includes techniques such as Structural Equation Modeling (SEM) implemented in SMART PLS 4 to identify key constructs influencing AI adoption and their impact on consumer attitudes and the decision-making processes for online purchases. The results obtained were used for accepting or rejecting the hypothesis formulated for the study.

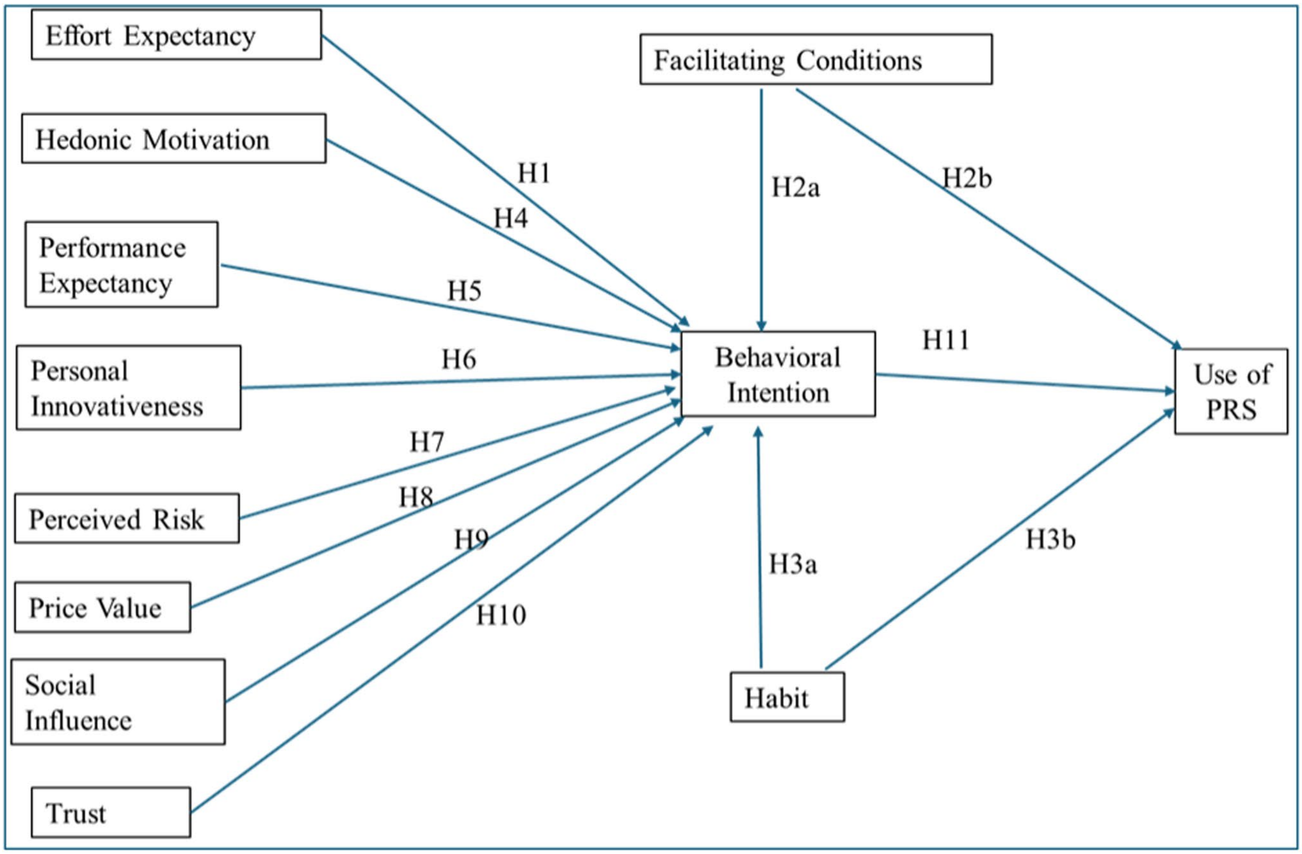

Fig. 1 Proposed conceptual model

4.2 Research instrument design and description

To analyse the effect of AI based PRS on the decision making of the online buyers, the primary data had to be collected. The research instrument chosen for this purpose was a constructed survey. Survey serves as a tool for gathering data, involving individuals responding to a predetermined sequence of questions [65]. This tool helps well when a significant amount of data is to be collected in restricted period [66]. For designing the survey prior work in the related area was referenced [67, 68] along with detailed study of the model to be used and its constructs. The constructs identified in the research were measured using established scales from prior research. These measurement scales provided reliability and validity in capturing users' perceptions and behaviors. Before distributing the questionnaire to the target sample, the pre-testing of the questionnaire was done with a smaller group of users and expert researchers. This pre-testing phase aimed to identify any ambiguities, errors, or areas for improvement in the questionnaire. Feedback from pre-testers was used to refine the questionnaire for clarity and relevance.

The survey instrument incorporated questions seeking demographic information about the participants and thereafter about their experience in online shopping and how it became better with AI enabled assistance in the form of personalized recommendation systems and what motivated them to use technology as part of online shopping and other such questions to finally understand their intentions to use personalized recommendation systems when they shop online.

The questions selected were rating questions and the scale chosen for measuring the responses was the 5 point Likert-style. Respondents were asked to respond on their agreement or disagreement with the presented statement [65]. The responses ranged from Strongly Agree (5) to Strongly Disagree (1). The rating scale's neutral point allowed respondents to express their ambiguity, which can mean they don't wish to express their opinions [65]. The survey instrument is depicted in Table 1.

Table 1 Items used in survey instrument

Construct	Variables	Items
Performance expectancy—PE	PE1	I believe that personalized recommendation systems in online retail significantly enhance my shopping experience
	PE2	Personalized recommendation systems help me discover products that align better with my preferences and needs
	PE3	Using personalized recommendation systems saves me time in searching for products I'm likely to purchase
	PE4	Personalized recommendation systems enhance my confidence in making purchase decisions online
Effort expectancy—EE	EE1	I find it easy to navigate and use personalized recommendation systems on online retail websites
	EE2	Using personalized recommendation systems on online retail platforms is straightforward and intuitive
	EE3	Personalized recommendation systems in online retail make my shopping experience more convenient
Social influence—SI	SI1	When I see that products or services are recommended to me based on the preferences of other users, I feel more confident in my purchasing decisions
	SI2	I am influenced by the popularity of products or services recommended by other consumers when making my online shopping decisions
	SI3	Personalized recommendation systems are more appealing to me when I see that they have been endorsed or shared by friends or peers on social media
Facilitating conditions—FC	FC1	Online retailers offer clear instructions and guidance on how to make the most of personalized recommendation systems
	FC2	Online retail platforms regularly update and improve the features related to personalized recommendation systems, making them more user-friendly
Hedonic motivation—HM	HM1	I derive satisfaction from discovering unique and personalized recommendations that enhance my online shopping experience
	HM2	The use of personalized recommendation systems in online retail makes my shopping interactions more enjoyable and engaging
Price value—PV	PV1	Personalized recommendation systems often lead me to discover items that offer good value for their price
	PV2	I feel that using personalized recommendation systems in online retail enables me to make more cost-effective purchase decisions
Habit—H	H1	Without consciously thinking about it, I often rely on personalized recommendation systems to discover products or services online
	H2	I find that I instinctively trust and act upon personalized suggestions without much thought
Trust—TR	TR1	I have confidence that the personalized recommendations I receive are based on my actual preferences and behaviors
	TR2	I trust that the personalized suggestions provided to me are in my best interest as a consumer
	TR3	Trust is an essential factor for me when it comes to accepting and adopting personalized customer recommendations
Perceived Risk—PR	PR1	I have concerns about the privacy and security of my personal data when using personalized recommendation systems in online retail
	PR2	The possibility of receiving biased or manipulated recommendations concerns me when using personalized suggestions
	PR3	I perceive a risk that relying on personalized recommendation systems may result in a less diverse and dynamic shopping experience
Personal innovativeness—PI	PI1	I have a natural curiosity to explore and experiment with new features and functionalities offered by online retail platforms
	PI2	I feel comfortable using technology and innovation in my online shopping experiences
Behavioral intention—BI	BI1	I intend to use Personalized Recommendation systems in online shopping in near future
	BI2	I will always try to use Personalized Recommendation systems in online shopping in daily life
	BI3	I will recommend others to use Personalized Recommendation systems in online shopping
Usage behaviour—UB	UB1	The use of personalized recommendation systems is now a well-established part of my online shopping decision-making process
	UB2	The use of personalized recommendation systems significantly influences my overall satisfaction during online shopping experiences?

4.3 Sample and sampling techniques

The study applied a non-probability sampling technique called convenience sampling, chosen for its practicality and accessibility. It allowed for effective data collection from respondents in the Delhi-NCR region who had experience with AI-powered PRS. The target population for this study consisted of residents of Delhi-NCR who were actively engaged in online shopping and had experience with Persoanlized Recommendation systems. The questionnaire reached people of all age groups and diverse backgrounds but belonging to Delhi-NCR region only. The period for data collection spanned over four months from September 2023 to December 2023.

To ensure that the respondents met the inclusion criteria, they were required to self-identify as residents of Delhi-NCR, active online shoppers, and aware of personalizedd recommendation systems. To encourage participation, the research team promoted the questionnaire through multiple posts and reminders on social media platforms. These efforts aimed to reach a larger and diverse pool of participants. Responses collected were regularly reviewed for completeness and accuracy to eliminate any incomplete or inconsistent data. Invalid or duplicate responses were also identified and removed during data cleaning. The demographic profile of the respondents is in Table 2.

One respondent was a minor falling in the age-group "Under 18 years" and thus the data was not considered for final analysis. One record belonging to Age Group 65 or older was found to have missing values for the key parameters and was thus discarded.

Finally the selected sample consisted of 220 with data from individuals who stated that they indulge in online shopping and are familiar with Personalized Recommendation Systems and their role in purchase decisions.

5 Results and Analysis

5.1 Demographic Analysis

Demographic analysis of the sample indicates the following points:

(a) predominant presence of younger individuals, especially in the 18–24 age bracket, suggesting resonance with younger population, commonly characterized by significant connectivity and participation on digital platforms, which might have implications for digital marketing strategies and online engagement.
(b) Lower representation of older age groups could either point to a lesser relevance or a potential untapped market.
(c) Gender wise a relatively balanced mix of male and female respondents, with a slight skew towards male participants.
(d) A significant number of respondents identify as single, which might correlate with the younger age trend observed. This finding can be indicative of lifestyle preferences and priorities associated with single individuals, such as higher flexibility in certain types of consumption or a different approach to financial decisions compared to married counterparts.
(e) Highly educated respondents suggest a well-informed and critically thinking audience, potentially more receptive to detailed and sophisticated content.
(f) High number of full-time employed individuals and students in our respondent pool provides a dual perspective. The employed segment might indicate financial independence and different consumption patterns compared to students, who might be more price-sensitive and trend-oriented.

5.2 Quantitative Data Analysis

The proposed Conceptual Model is shown in Fig. 1. It shows 02 (two) dependent and 10 (ten) independent variables. The Dependent Variables are Behavioral Intention and Usage Behaviour (Use). The Independent Variables are performance expectancy—PE, effort expectancy—EE, social influence—SI, facilitating conditions – FC, hedonic motivation—HM, price value—PV, habit—H, trust—TR, perceived risk—PR and personal innovativeness—PI. Quantitative data analysis using PLS-SEM algorithm in SMART PLS 4 was implemented on the sample to study the effect of the latent varibales on the decision making capabilities of the user population indulged in online shopping in Delhi NCR.

Table 2 Demographic analysis of the data

Description	No of respondents		% of respondents
Age			
Under 18	1		0.45
18—24	90		40.91
25—34	62		28.18
35—44	27		12.27
45—54	38		17.27
55—64	1		0.45
65 or older	3		1.36
Total	**222**		
Gender			
Female		101	45.91
Male		118	53.64
Prefer not to say		1	0.45
Total		**220**	
Marital status			
Single		136	61.82
Married		81	36.82
Divorced		1	0.45
Widowed		2	0.91
Total		**220**	
Level of qualification			
Bachelor's Degree		63	28.64
Master's degree		92	41.82
Doctorate or Professional Degree		43	19.55
High School		22	10.00
Total		**220**	
Employment status			
Employed full-time		91	41.36
Employed part-time		9	4.09
Self-employed		10	4.55
Homemaker		6	2.73
Student		95	43.18
Retired		2	0.91
Unemployed		6	2.73
Other		1	0.45
Total		**220**	

The bold values indicate summation values for each category

A basic PLS-SEM path model was created using SMART PLS 4. The Basic Path model was reflective-reflective in nature and is depicted in Fig. 2.

After applying the PLS-SEM algorithm to the basic model, the resulting model is depicted in Fig. 3. It includes the measurement models (or outer models) that illustrate the relationships between the constructs and their indicators, along with the structural model showing the relationships among the constructs.

5.3 Measurement Model Estimation Results: Outer Loadings

Structural Equation Modelling (SEM), in the context of PLS analysis, initially seeks to confirm the reliability and validity of the measurement scales by analysing the measurement model. The measurement model serves as a diagnostic tool to assess the quality of the data in preparation for additional investigation. The main tests focus

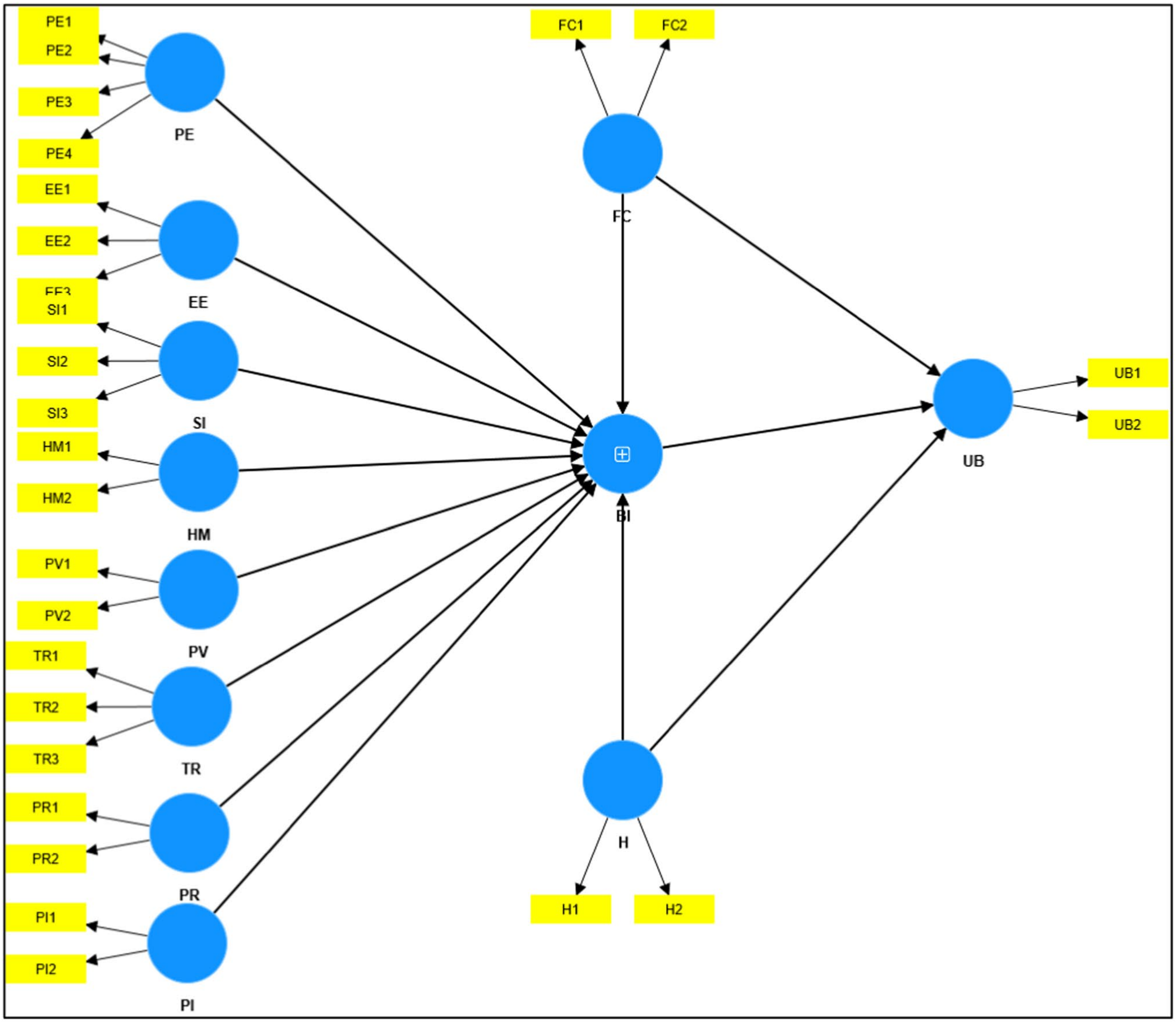

Fig. 2 Basic PLS-SEM path model

on validity and reliability, with specific categories including item reliability, internal reliability, convergent validity, and discriminant validity. Table 3 displays the measurement model values.

5.3.1 Reliability

Reliability is checked with the help of the outer loadings of the individual items, the values of which must be close to or greater than 0.7 [69, 70]. All loadings were found to confirm to the threshold except TR3, so this item was eliminated from the scale of measurement. Internal consistency is checked with Composite Reliability and Cronbach's alpha (rho_a and rho_c). The Cronbach alpha. rho_a and rho_c must be greater than the threshold values of 0.70 [71]. The reliability of the constructs was analyzed with two indicators, namely composite reliability and cronbach's alpha. The values were found to be above 0.7 as suggested [71], except Facilitating Conditions (FC) whose Cronbach alpha was 0.658 but its CR (rho_c) was 0.853, hence the construct reliability was established and the construct was not deleted.

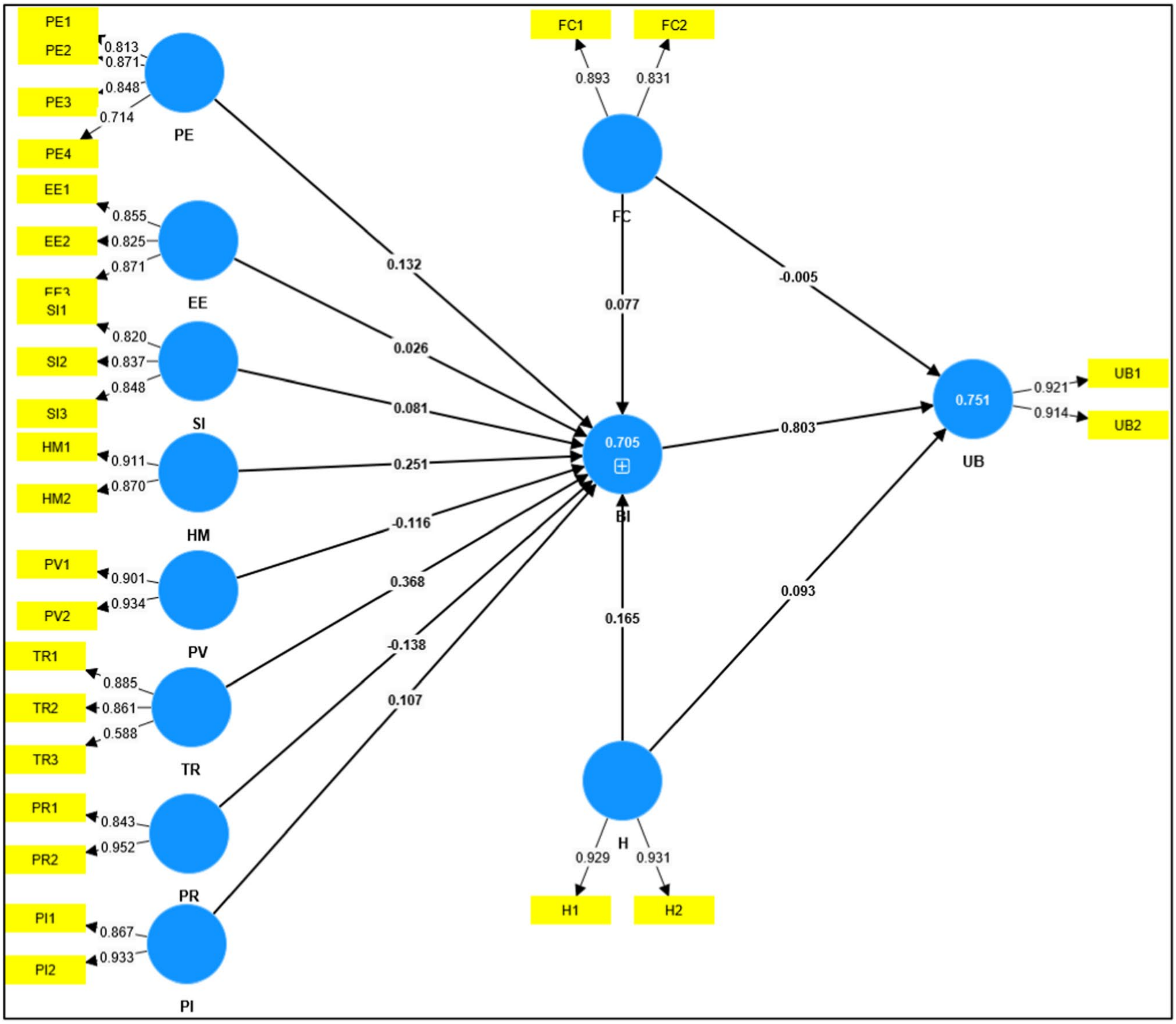

Fig. 3 Graphical output of PLS-SEM algorithm

5.3.2 Validity

Validity has two scales, convergent validity and discriminant validity. *Convergent validity* is checked with Average Variance Extracts (AVE). An AVE value of 0.50 or higher [72] is required for validation. For convergent validity, analyzed with AVE (Average Variance Extracted), all AVE values were greater than the threshold 0.50 as recommended [72] for all constructs. Hence, the model has acceptable convergent validity.

5.3.3 Discriminant validity

To assess whether the construct measures exhibit discriminant validity, we focus on the HTMT and Fornell-Larcker criteria. The HTMT (Heterotrait-Monotrait Ratio) matrix values are calculated on the grounds of absolute correlations. The Fornell-Larcker criterion asserts that, when evaluating the AVE alongside the squared correlations between constructs, the square root of the AVE for each construct should be greater than its maximum correlation with any other construct in the model. Table 4 shows the Discriminant Validity with HTMT results and Table 5 shows Discriminant Validity with Fornell and Larcker results. The diagonal values in Table 5 are showing the square root of the AVE and is highlighted in bold. Regarding HTMT, all correlation values among variables need to be less than 0.9, with a preference for values lower

Table 3 Reliability and validity values for the measurement model

Construct	Items	Loadings	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE	VIF
Performance expectancy—PE	PE1: I believe that personalized recommendation systems in online retail significantly enhance my shopping experience	0.813	0.827	0.829	0.886	0.662	2.167
	PE2: Personalized recommendation systems help me discover products that align better with my preferences and needs	0.871					2.554
	PE3: Using personalized recommendation systems saves me time in searching for products I'm likely to purchase	0.848					1.995
	PE4: Personalized recommendation systems enhance my confidence in making purchase decisions online	0.714					1.355
Effort expectancy—EE	EE1: I find it easy to navigate and use personalized recommendation systems on online retail websites	0.855	0.812	0.839	0.887	0.723	1.858
	EE2: Using personalized recommendation systems on online retail platforms is straightforward and intuitive	0.825					1.867
	EE3: Personalized recommendation systems in online retail make my shopping experience more convenient	0.871					1.668
Social influence—SI	SI1: When I see that products or services are recommended to me based on the preferences of other users, I feel more confident in my purchasing decisions	0.82	0.784	0.786	0.874	0.697	1.453
	SI2: I am influenced by the popularity of products or services recommended by other consumers when making my online shopping decisions	0.837					1.8
	SI3: Personalized recommendation systems are more appealing to me when I see that they have been endorsed or shared by friends or peers on social media	0.848					1.81
Facilitating conditions—FC	FC1: Online retailers offer clear instructions and guidance on how to make the most of personalized recommendation systems	0.893	0.658	0.678	0.853	0.744	1.317
	FC2: Online retail platforms regularly update and improve the features related to personalized recommendation systems, making them more user-friendly	0.831					1.317
Hedonic motivation—HM	HM1: I derive satisfaction from discovering unique and personalized recommendations that enhance my online shopping experience	0.911	0.742	0.758	0.885	0.794	1.533
	HM2: The use of personalized recommendation systems in online retail makes my shopping interactions more enjoyable and engaging	0.87					1.533
Price value—PV	PV1: Personalized recommendation systems often lead me to discover items that offer good value for their price	0.901	0.815	0.837	0.915	0.843	1.897
	PV2: I feel that using personalized recommendation systems in online retail enables me to make more cost-effective purchase decisions	0.934					1.897
Habit—H	H1: Without consciously thinking about it, I often rely on personalized recommendation systems to discover products or services online	0.929	0.843	0.844	0.927	0.865	2.136
	H2: I find that I instinctively trust and act upon personalized suggestions without much thought	0.931					2.136

Table 3 (continued)

Construct	Items	Loadings	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE	VIF
Trust—TR	TR1: I have confidence that the personalized recommendations I receive are based on my actual preferences and behaviors	0.885	0.78	0.785	0.9	0.819	1.689
	TR2: I trust that the personalized suggestions provided to me are in my best interest as a consumer	0.862					1.689
	TR3: Trust is an essential factor for me when it comes to accepting and adopting personalized customer recommendations	0.588					
Perceived risk—PR	PR1: I have concerns about the privacy and security of my personal data when using personalized recommendations systems in online retail	0.795	0.803	0.841	0.881	0.712	1.799
	PR2: The possibility of receiving biased or manipulated recommendations concerns me when using personalized suggestions	0.888					1.931
	PR3: I perceive a risk that relying on personalized recommendations may result in a less diverse and dynamic shopping experience	0.846					1.576
Personal innovativeness—PI	PI1: I have a natural curiosity to explore and experiment with new features and functionalities offered by online retail platforms	0.867	0.773	0.832	0.896	0.811	1.658
	PI2: I feel comfortable using technology and innovation in my online shopping experiences	0.933					1.658
Behavioral intention—BI	BI1: I intend to use Personalized Recommendation systems in online shopping in near future	0.9	0.904	0.904	0.94	0.838	2.526
	BI2: I will always try to use Personalized Recommendation systems in online shopping in daily life	0.934					3.559
	BI3: I will recommend others to use Personalized Recommendation systems in online shopping	0.913					3.021
Usage behaviour—UB	UB1: The use of personalized recommendation systems is now a well-established part of my online shopping decision-making process	0.921	0.813	0.814	0.914	0.842	1.882
	UB2: The use of personalized recommendation systems significantly influences my overall satisfaction during online shopping experiences?	0.914					1.882

Table 4 Discriminant validity—HTMT criteria

	BI	EE	FC	H	HM	PE	PI	PR	PV	SI	TR	UB
BI												
EE	0.607											
FC	0.844	0.723										
H	0.783	0.44	0.817									
HM	0.82	0.721	0.953	0.708								
PE	0.711	0.876	0.662	0.551	0.724							
PI	0.548	0.449	0.517	0.301	0.632	0.624						
PR	0.314	0.386	0.346	0.268	0.575	0.35	0.61					
PV	0.665	0.608	0.791	0.633	1.001	0.615	0.519	0.461				
SI	0.706	0.737	0.802	0.657	0.759	0.721	0.442	0.298	0.785			
TR	0.889	0.59	0.893	0.965	0.805	0.653	0.522	0.394	0.748	0.711		
UB	1.007	0.579	0.785	0.77	0.826	0.734	0.506	0.31	0.7	0.681	0.88	

Table 5 Discriminant Validity –Fornell and Larcker

	BI	EE	FC	H	HM	PE	PI	PR	PV	SI	TR	UB
BI	0.916											
EE	0.536	0.851										
FC	0.657	0.528	0.862									
H	0.683	0.379	0.616	0.93								
HM	0.677	0.569	0.664	0.568	0.891							
PE	0.617	0.733	0.492	0.463	0.571	0.814						
PI	0.469	0.358	0.379	0.242	0.478	0.486	0.901					
PR	0.281	0.317	0.249	0.238	0.447	0.274	0.456	0.844				
PV	0.576	0.5	0.582	0.532	0.774	0.507	0.407	0.369	0.918			
SI	0.597	0.591	0.571	0.535	0.58	0.59	0.352	0.244	0.629	0.835		
TR	0.747	0.481	0.65	0.784	0.62	0.528	0.407	0.32	0.601	0.552	0.905	
UB	0.864	0.482	0.581	0.639	0.645	0.602	0.404	0.261	0.575	0.549	0.704	0.918

than 0.8 [69]. While in Fornell and Larcker, the diagonal value must be greater than those in their respective column. The results of Fornell and Larcker are all satisfying the criteria. But in HTMT some values did not confirm to the standard. Based on Fornell and Larcker results the discriminant validity was confirmed.

5.4 Structural Model

The structural model defines the relationships between the constructs in the research framework. The main presumption backing the structural model analysis is that it will work with the measurement's diagnostic instruments, such as validity and reliability. For instance, multicollinearity works best in this structural model's crucial regression fitness.

5.4.1 Multicollinearity

Multi-collinearity is evaluated to assess the dataset for various regression assumptions [73]. An examination of the variance inflation factor (VIF) was performed to determine whether multi-collinearity existed in the data. Results depicted in Table 3 show that all VIFs were less than the threshold of 10.0 recommended by [72]. Hence there is no issue of multi-collinearity.

5.4.2 Common method bias

Common Method Variance (CMV) bias refers to a systematic error introduced during data collection, where the measurement method influences respondents' answers, potentially leading to skewed or inaccurate research outcomes. CMV can be checking using the VIF values. VIF values of 3.3 or lower indicate that the model is free from bias. According to Table 3, most VIF values fall below 3.3, suggesting that the model is not affected by common method bias. However, one value falls between 3.3 and 5, which indicates a very low level of method variance bias.

5.4.3 Path Coefficients

Path Coefficients in the Structural Model indicate the strength of the relationships between the associated variables. Table 6 presents the path coefficients for the Structural Model.

Hence, as per the Structural Model, Behavioral Intention is a strong predictor for Usage Behaviour. While Facilitating Conditions have a negligible negative impact on Usage Behaviour and Habit has a negligible positive impact on Usage Behaviour. With respect to Behavioral Intention, Hedonic Motivation, Trust, Habit and Performance Expectancy are strong predictors. The factors of Effort Expectancy, Facilitating Conditions, Personal Innovativeness, and Social Influence have a slight positive influence on Behavioral Intention, while Perceived Risk shows a slight negative influence.

As a general rule, for sample sizes of about 1,000 observations, standardized path coefficients exceeding 0.20 are typically significant, while values below 0.10 are usually not significant. Hence to further check the data Bootstrapping process was applied onto the basic PLS-SEM Model with 10,000 subsamples. The results of this step helped in checking the statistical significance of each of the coefficients and the paths. The model after Bootstrapping is given in Fig. 4

The bootstrapped PLS-SEM model visualized in the figure highlights the p-values for each path and item loading in the analysis. These are shown in Table 8. Most paths and loadings show p-values of 0.000, suggesting statistical significance. However, p values of certain paths, like those leading BI from EE(0.477), SI(0.099), PV(0.122), PR(0.066), FC(0.90) are greater than 0.05, hinting at potential statistical insignificance in these relationships within the model. Path leading to UB from FC(0.459) is statistically insignificant.

Therefore the statistically significant paths leading to BI are from PE (0.022), TR (0.000), HM(0.007) and PI(0.013). For UB, the statistically significant paths are BI(0.000) and H(0.041).

5.5 Goodness of Fit

5.5.1 R^2 and Adjusted R^2 values of the dependent variables

R-squared values indicate the percentage of variance in the dependent variable that is explained by the independent variables. Adjusted R-squared provides a more accurate measure of the model's goodness of fit, particularly with multiple predictors, by penalizing unnecessary variables and factoring in the number of predictors. R squared and adjusted R squared values differ in that the former assumes that every independent variable taken into account has an impact on the model's outcome, while the latter only takes into account the independent variables that actually have an impact on the model's performance. The R^2 and Adjusted R^2 values of the BI and UB are given in Table 7.

Table 6 Path coefficients first order constructs

	Path coefficients
BI—> UB	0.803
EE—> BI	0.012
FC—> BI	0.093
FC—> UB	− 0.005
H—> BI	0.185
H—> UB	0.093
HM—> BI	0.238
PE—> BI	0.143
PI—> BI	0.093
PR—> BI	− 0.099
PV—> BI	− 0.109
SI—> BI	0.079
TR—> BI	0.337

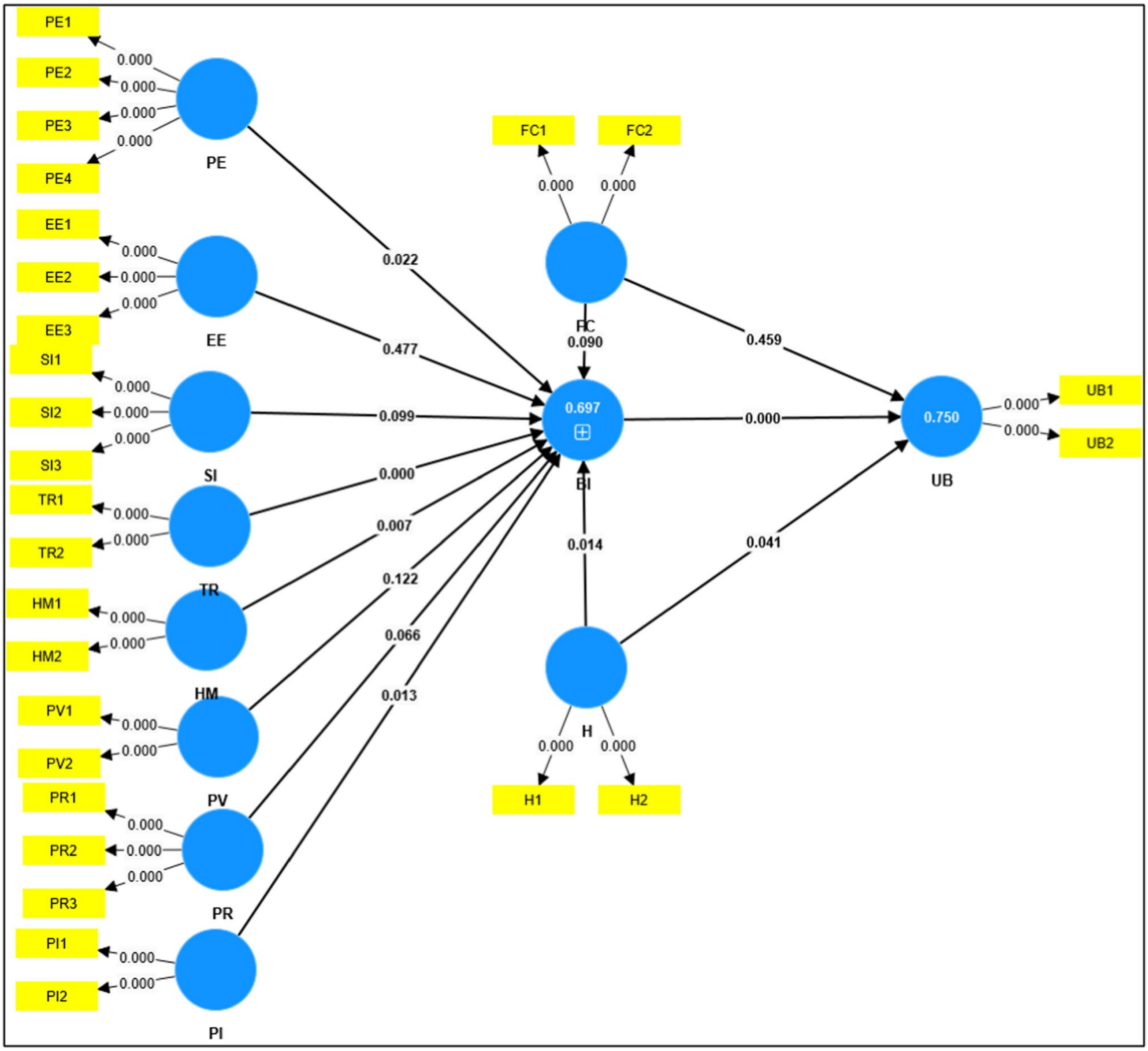

Fig. 4 PLS-SEM model post bootstrapping process

Table 7 R^2 and adjusted R^2 values of dependent or endogenous variables

	R-square	R-square adjusted
BI	0.705	0.691
UB	0.751	0.747

- The R^2 values for BI is 0.705, and for UB, it is 0.751, suggesting that the model explains a significant part of the variance in these constructs.
- Adjusted R^2 is 0.691 for BI and 0.747 for UB. These high values, indicate a strong model fit, as they account for the number of predictors and avoid overestimation that can occur with multiple variables.

Table 8 Significance testing results of structural model path coefficients

Hypothesis	Path coefficients	t values	p values	R^2	f2	Significance (p < 0.05)?
Hypothesis 1: EE—> BI	0.004	0.059	0.477		0	Not Significant
Hypothesis 2a: FC—> BI	0.1	1.342	0.09		0.014	Not Significant
Hypothesis 2b: FC—> UB	− 0.005	0.103	0.459		0	Not Significant
Hypothesis 3a: H—> BI	0.169	2.191	0.014		0.031	Significant
Hypothesis 3b: H—> UB	0.093	1.742	0.041		0.017	Significant
Hypothesis 4: HM—> BI	0.231	2.476	0.007		0.049	Significant
Hypothesis 5: PE—> BI	0.147	2.007	0.022		0.026	Significant
Hypothesis 6: PI—> BI	0.119	2.22	0.013		0.027	Significant
Hypothesis 7: PR—> BI	− 0.07	1.505	0.066		0.011	Significant
Hypothesis 8: PV—> BI	− 0.091	1.164	0.122		0.009	Not Significant
Hypothesis 9: SI—> BI	0.089	1.289	0.099		0.012	Not Significant
Hypothesis 10: TR—> BI	0.306	3.86	0		0.091	Significant
Hypothesis 11: BI—> UB	0.803	19.071	0	**0.697**	1.147	Significant
UB				**0.75**		
SRMR						**0.07**

The bold values represent the prominent results

5.6 Summary of hypothesis

The structural model was analyzed to evaluate the proposed hypotheses and examine the path coefficients. To increase the stability of the results Bootstrapping was applied. The SRMR (Standardized Root Mean Square) value obtained was 0.07 less than the proposed standard (0.08) [69] suggesting a good fit. The R^2 values of the Endogenous variables UB and BI are 0.75 and 0.697 respectively suggesting higher explanatory power of the model. Table 8 shows the final results listing the verified hypothesis and the size of their effect.

Usage Behaviour and Behavioral Intention both can be significantly explained as is evident from the R square values. The effect size *f* 2 for all structural model relationships depict that the values of 3a, 3b, 5, 6, 7, 10 lie between 0.015 and 0.035 [74] and the rest are either above or below this range. This suggests that where the ratios were significant the effect size was within bounds, except for 11 where the value is more. Out of 13 relations 8 are significant. The model has a good fit since the SRMR is 0.07, well below 0.08 [75].

5.7 Predictive relevance

The model's predictive capacity was further calculated.The results are tabulated in Table 9.

The results, as presented in Table 9, provide key insights into the model's predictive power [70]. The breakdown of the results is as below:

1. *Q^2 Predict (Predictive Relevance)* The Q^2 values for BI (0.652) and UB (0.563) are above 0, indicating that the model has predictive relevance for both latent variables. A Q^2 value greater than 0 suggests that the model is capable of reliably predicting the latent variables. In this case, the higher value for BI implies a stronger predictive capability for Behavioral Intention compared to Usage Behavior.
2. *RMSE (Root Mean Square Error)* The RMSE values are 0.596 for BI and 0.667 for UB. RMSE measures the model's prediction error, with lower values indicating better predictive accuracy. The slightly low RMSE values here suggest that the model's predictions for both BI and UB are reasonably accurate, with a slightly better accuracy for BI.

Table 9 Predictive summary of the latent variables

	Q^2predict	RMSE	MAE
BI	0.652	0.596	0.463
UB	0.563	0.667	0.514

3. *MAE (Mean Absolute Error)* MAE values are 0.463 for BI and 0.514 for UB. Like RMSE, MAE is another measure of prediction accuracy, quantifying the average magnitude of the errors in a set of predictions, without considering their direction. Lower MAE values indicate more accurate predictions. The results show that the model predicts Behavioral Intention with slightly higher accuracy than Usage Behavior.

6 Discussions

The transformative impact of AI on retail, particularly online shopping, warrants exploration. In this study, we have investigated this influence using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The study has been based on the online purchase decision-making process of the consumers in Delhi-NCR region. Implementing a Structural Equation Modelling (SEM) using SmartPLS showed that eight out of thirteen proposed hypotheses were supported (Hypothesis 3a, Hypothesis 3b, Hypothesis 4, Hypothesis 5, Hypothesis 6, Hypothesis 7, Hypothesis 10, Hypothesis 11).

One of the key findings of this study is Hypothesis 11 that emphasises strong impact of Behavioral Intention (BI) on Usage Behavior (UB). This result is consistent and thus supports previous research by [60]. Strong predictive relevance has been demonstrated by the path coefficient between BI and UB, which was very significant (0.803; $R^2 = 0.751$). This suggests that a strong indicator of actual usage behavior is consumers' aspirations to use AI in online purchasing. R^2 Values of 0.705 for BI and 0.751 for UB are indicativen of a high explanatory power of the model for these variables.

Trust in AI Systems Plays a Critical Role as it has a major impact on behavioral intention (Hypothesis 10). The substantial t-value and strong path coefficient (0.306) indicate that consumers' willingness to adopt AI for online purchasing is contingent upon their level of trust. This result has been validated and supports previous research by [60].

The study discovered that the three main factors determining behavioral intention are Personal Innovativeness (Hypothesis 6), Habit (Hypothesis 3b), and Hedonic Motivation (Hypothesis 4). This emphasizes how crucial AI delight, habitual AI system use, and openness to technology innovation are in influencing how customers engage with online retailers. Hupothesis 6 support previous research by [61]. Hypothesis 4 validates previous research by [56]. Hypothesis 3 examined the relationship between habit and use, both directly (Hypothesis 3a) and indirectly through Behavioral Intention (Hypothesis 3b), has been supported and validated previous research by [46, 56].

It has been observed that PE positively influenced behavioral intention (Hypothesis 5), indicating that adoption of AI systems is motivated by conviction in their efficacy. This hypothesis has been validated and supports previous research by [59, 60]. Perceived Risk (PR), on the other hand, showed a marginally significant negative impact on behavioral intention (Hypothesis 7), suggesting that consumers are hesitant to use AI when they shop online. The hypothesis has been validated in this study and supports previous research by [62].

The study also shows that Social Influence (Hypotheiss 9) and Effort Expectancy (Hypothesis 1) had lessened, non-significant effects on Behavioral Intention. Loadings for Effort Expectancy ranged from 0.825 to 0.871, but the path coefficient to BI was low at 0.012, indicating a minimal direct effect. This suggests that social influences and the usability of AI systems may not be the main variables when making judgments about online purchase. These results are in contrast with earlier research i.e. studies of [57] and [58] for Hypothesis 1 and results of [59] and [58] for hypothesis 9.

Facilitating conditions similarly influence neither behavioral intention (Hypothesis 2a) nor use (Hypothesis 2b) and thus does not validate earlier research by [44].

As per research by [63] and [56], Price Value positively influences the Behavioral Intention, but this hypothesis is not supported in the current study. Thereby proving the converse that for consumers of Delhi NCR, price of technology does not impact their intention to use AI for online shopping (Hypothesis 8).

With Q2 values of 0.652 and 0.563 for BI and UB, respectively, the model had a significant predictive relevance. Furthermore, the model's good fit to the observed data (SRMR value of 0.07) suggests that the conclusions are reliable. The demographic analysis of the study offers a rich backdrop, demonstrating various reactions across gender, marital status, educational level, and employment status. This variety highlights how widely the results can be applied to different demographic groups. The research provides a statistically robust and insightful analysis into the factors influencing AI's role in online shopping decisions in Delhi-NCR, backed by strong empirical evidence and thorough statistical validation. It suggests that elements like simplicity of use and social influence might not be as important as they formerly were, but it emphasizes the crucial roles of trust, enjoyment, habitual usage, and innovation openness. E-commerce platforms may optimize user experiences and increase AI adoption with the help of these insights.

6.1 Theoretical implications

This study advances and supports earlier studies focussed towards—a comprehensive analysis of the factors that affect the impact of Artificial Intelligence on online purchase decision-making through the UTAUT 2 framework in the Delhi-NCR region. The significant results from the hypothesis testing highlight the crucial role of factors like Habit, Hedonic Motivation, Performance Expectancy, Perceived Risk, Trust, and Personal Innovativeness in shaping Behavioral Intention towards AI in online shopping. The findings suggest a need for marketers and developers to focus on enhancing the user experience and building trust in AI technologies to increase adoption rates. The insignificance of Effort Expectancy, Facilitating Conditions, and Social Influence in influencing Behavioral Intention and Usage Behavior points towards the unique characteristics of the Delhi-NCR market. This could imply a more discerning and independent consumer base in this region, which relies less on social cues or ease of use, and more on personal habits and the intrinsic value offered by AI in online shopping. Strong Predictive Power and Robustness of the UTAUT2 Model has been highlighted. The goodness of fit analysis, including high R^2 and Adjusted R^2 values, indicates the model's robustness in explaining the variance in Behavioral Intention and Usage Behavior. The model's strong predictive relevance, as indicated by satisfactory Q^2 predict, RMSE, and MAE values, further validates its effectiveness in forecasting consumer responses to AI in online shopping. This aspect is particularly valuable for anticipating market trends and consumer preferences.

6.2 Practical implications

The model not only provides academic insights into the factors influencing AI adoption in online shopping but also offers practical implications for businesses and policymakers. The ability to predict consumer behavior based on these factors is invaluable for strategic decision-making and for fostering a more AI-friendly market environment in the Delhi-NCR region. These insights provide a strategic edge to businesses in tailoring their marketing and product development strategies. Emphasizing on aspects that significantly influence consumer behavior can lead to more effective marketing campaigns and product features that resonate with the target audience. The significant impact of Personal Innovativeness suggests a receptive market for new technologies. This can encourage businesses to invest in innovative AI features, knowing that a segment of the market is likely to respond positively. The study's findings can assist policymakers in understanding the consumer dynamics around AI in online shopping, enabling them to formulate policies that foster technological advancement while addressing consumer needs and concerns.

7 Conclusion, limitations and directions for future research

The study successfully identified critical factors influencing consumers' adoption of AI in online shopping within the Delhi-NCR region, using the UTAUT 2 framework. Significant factors like Habit, Hedonic Motivation, Trust, and Personal Innovativeness emerged as pivotal in shaping consumers' Behavioral Intentions towards AI in online shopping. Contrarily, constructs like Effort Expectancy, Facilitating Conditions, and Social Influence were found to have lesser impact. The robustness of the model was established through its good fit and predictive relevance. High R^2 and Adjusted R^2 values indicated that a significant proportion of the variance in Behavioral Intention and Usage Behavior was explained by the model. Moreover, satisfactory Q^2 predict, RMSE, and MAE values underlined the model's capability in forecasting consumer behavior towards AI in online shopping.

The study underscores the unique consumer dynamics of the Delhi-NCR region, where personal habits and intrinsic motivations play a more significant role in technology adoption than societal influence or perceived ease of use. This highlights the importance of localized strategies in technology implementation and marketing.

In conclusion, this study contributes to the understanding of AI adoption in online shopping, offering a comprehensive view of the factors that drive consumer behavior in the context of new technological advancements. It provides a framework for businesses to strategize effectively and paves the way for future research in this evolving field.Limitations: The study has some limitations in terms of the generalizability and comprehensiveness of its findings. Focusing solely on the Delhi-NCR region limits the applicability of the results to other areas with different cultural or economic contexts. Additionally, the study did not explore all potential factors, such as economic or psychological influences, which may affect the completeness of the analysis. Contradictory findings on Social Influence and Effort Expectancy, compared to previous research, suggest potential issues or contextual differences. The lack of significance for Price Value as a factor, contrary to established studies, highlights the unique consumer behavior in this region, which may not be applicable elsewhere.

Future Scope The study opens avenues for further investigation into the role of AI in varying cultural and demographic contexts. Future research could explore the long-term effects of AI on consumer behavior, ethical considerations of AI in e-commerce, and comparative studies across different regions. Additionally, investigating the impact of evolving AI technologies and the interplay with emerging online shopping trends could provide deeper insights into the dynamics of e-commerce. In addition implementation of methods such as implementation of an integrated model based on the theory of planned behaviour for testing the model proposed in [76] by implying SEM-ANN deep learning techniques, dual-stage SEM-ANN approach [76, 77] or Two-step system GMM [78].

Author contributions Dr. Rinku Sharma Dixit: Writing–original draft, Methodology Conceptualization and Execution, Validation of Results. Dr. Shailee Lohmor Choudhary: Formal Data Analysis, Visualization, Investigation. Dr. Nikhil Govil: Data Collection, Resources collection, Supervision All authors reviewed the manuscript.

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Data availability The data is available with the authors and available on request.

Declarations

Ethics approval and consent to participate This study was conducted according to the guidelines laid down in the Declaration of Helsinki, and the study protocol was approved by the LBS Research Ethics Committee, Liverpool Business School. Electronic informed consent was obtained from all participants on the first page of the questionnaire.The ethics approval form signed by University Guide on 5th Nov 2023, is attached in "Related Files".

Consent for publication Not applicable.

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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